

Characteristics of production database workloads and the TPC benchmarks

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There has been very little empirical analysis of any real production database workloads. Although the Transaction Processing Performance Council benchmarks C (TPC-C™) and D (TPC-D™) have become the standard benchmarks for on-line transaction processing and decision support systems, respectively, there has not been any major effort to systematically analyze their workload characteristics, especially in relation to those of real production database workloads. In this paper, we examine the characteristics of the production database workloads of ten of the world's largest corporations, and we also compare them to TPC-C and TPC-D. We find that the production workloads exhibit a wide range of behavior. In general, the two TPC benchmarks complement one another in reflecting the characteristics of the production workloads, but some aspects of real workloads are still not represented by either of the benchmarks. Specifically, our analysis suggests that the TPC benchmarks tend to exercise the following aspects of the system differently than the production workloads: concurrency control mechanism, workload-adaptive techniques, scheduling and resource allocation policies, and I/O optimizations for temporary and index files. We also re-examine Amdahl's rule of thumb for a typical data processing system and discover that both the TPC benchmarks and the production workloads generate on the order of 0.5 to 1.0 bit of logical I/O per instruction, surprisingly close to the much earlier figure.

The Transaction Processing Performance Council (TPC) benchmarks C (TPC-C[™])¹ and D (TPC-D[™])² have emerged as the *de facto* standard benchmarks for on-line transaction processing (OLTP) systems and decision support systems (DSS),

respectively. By establishing objectives that are easily measurable and repeatable, such standard benchmarks define a transparent playing field and focus attention on what the benchmarks consider to be important. However, the real utility of the benchmarks is determined by whether they represent the workloads of interest. To effectively make use of a benchmark, therefore, we have to carefully evaluate its characteristics against those of the target workloads to understand how closely they correspond. Although the TPC-C and TPC-D benchmarks have become widely accepted and, as a result, are heavily used for both systems design and marketing, there has not been any major effort to empirically determine their workload characteristics, let alone to establish how representative their characteristics are of real workloads.

In fact, there has been very little empirical analysis of any real production database workloads. This reflects the fact that production systems are by definition critical to the proper functioning of an organization, so that it is very difficult to get access to them for the purpose of conducting a scientific study, especially if the study requires any software changes or if data are to be collected and removed from the system. Therefore, although the hallmark of a good benchmark is that it should capture all the essential characteristics of the workload of interest without undue complexity, we often do not have a clear pic-

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ture of the characteristics of the target workload. This lack of information is highly undesirable because a poorly designed benchmark may impede real progress in the field if it is not realistic and end up focusing energy and attention on issues that do not often arise in production environments.

In this research, we use trace-driven simulations^{3,4} to empirically examine the characteristics of the peak production database workloads of ten of the world's largest corporations as well as workloads similar to the TPC-C and TPC-D benchmarks. Our main focus in this paper is on what we call descriptive system-level characteristics. These characteristics are the logical properties of a workload that a user or system administrator can readily understand and relate to without requiring detailed knowledge of the internals of the system. We compare and contrast such characteristics of the production workloads with those of the TPC benchmarks, paying special attention to any performance implications. In a companion paper,⁵ we examine in detail the I/O reference behavior of the workloads.

The traces used in this study were collected on systems running IBM's industrial-strength DATABASE 2* (DB2*) relational database management system (DBMS) and, to the best of our knowledge, represent by far the most complete and diverse set of production workloads ever reported in the literature. We cannot overemphasize the amount of time, effort, and cost that these traces represent. This research would not have been possible without the support and help of many. Note that because our TPC benchmark setups have not been audited per the benchmark specifications, our benchmark workloads should only be referred to as TPC-like. In the rest of this paper, when the terms TPC-C and TPC-D are used to refer to our benchmark workloads, they should be taken to mean TPC-C-like and TPC-D-like, respectively.

Our analysis indicates that in some cases, the TPC benchmarks fall reasonably within the range of real workload behavior, and in other cases, they are not representative of real workloads. Some of our findings are (1) TPC-C tends to have longer transactions and fewer read-only transactions than the production workloads, whereas some of the transactions done by TPC-D are much longer but are read-only and are run serially, (2) the production workloads have I/O demands that are much more bursty than the TPC benchmarks, (3) unlike TPC-C, which has very regular transactions, and TPC-D, which has long que-

ries that are run serially, the production workloads tend to have many concurrent and diverse transactions, and (4) TPC-C has no I/O activity involving temporary objects, whereas most of the references for TPC-D are directed at index objects.

The next section of this paper contains a brief overview of previous work in the area of workload characterization and analysis. The third section discusses our methodology and describes the traces that we use. The characteristics of our workloads are presented in the fourth section. Concluding remarks are then given. Because of space constraints, we can only highlight some of the results of our analysis in this paper. More detailed graphs and data are available from our Web site⁶ and in References 5 and 7.

Related work

There have been several published studies of the reference behavior of database workloads, but mostly for hierarchical and network databases. See, for instance, References 8 through 16. For a more complete bibliography, the reader is referred to Reference 5. Unfortunately, most of these studies rely on data collected at one or two installations. Furthermore, they do not provide descriptive characteristics of the workloads being analyzed, even though the reference behavior clearly depends on the workload imposed on the database. Without knowing the kinds of workload that are being examined, interpreting the results of the studies is very difficult. Consequently, there seem to be conflicting conclusions as to whether locality or sequentiality is present in the database reference stream. The work reported by Zivkov and Smith,¹⁶ which investigated design issues in disk caches using data from commercial installations, is one of the notable exceptions that provides some characteristics of the workloads analyzed. In addition, a recent study of lock contention in database systems contains some transaction statistics from commercial DB2 installations.¹⁷

Though the TPC-C and TPC-D² benchmarks have clearly been extensively studied and optimized by both database and system vendors, there has not been any systematic attempt to characterize these workloads empirically and to compare their characteristics with those of production database workloads. On the basis of static analysis of accesses to tables, Leutenegger and Dias¹⁸ looked at the data access skew of TPC-C. The paper by Tsuei et al.¹⁹ contains an empirical study of how the database size, buffer size, and the number of CPUs affect the

throughput and buffer hit rate of TPC-C on symmetric multiprocessors (SMPs). Given that business applications are increasingly developed on standard business application systems commonly known as Enterprise Resource Planning (ERP) systems, Doppelhammer et al.²⁰ examined the performance of TPC-D queries when implemented on such systems. Recently, Hsu et al.²¹ analyzed the query plans taken from certified TPC-D setups and considered the potential benefit of off-loading TPC-D operations to storage systems with embedded processors.

File usage characteristics in commercial computing environments are studied in the paper by Ramakrishnan et al.,²² but most of the work in this area has focused on academic environments (e.g., see References 23–27). Several other studies have focused on the effectiveness of caching in the file system.^{28,29} There has also been a large body of work on characterizing scientific workloads in parallel and supercomputing environments. Again, we refer the interested reader to Reference 5 for a more detailed bibliography.

Methodology

The methodology used in this paper is trace-driven simulation.^{3,4} In trace-driven simulation, relevant information about a system is collected while the system is handling the workload of interest. This is referred to as tracing the system and is usually achieved either by using hardware probes or by instrumenting the software. In the second phase, the resulting trace of the system is played back to drive a model of the system under study. In other words, trace-driven simulation is a form of event-driven simulation where the events are taken from a real system operating under conditions similar to the ones being simulated. More comprehensive discussions of this technique and its strengths and weaknesses can be found in References 3 and 4.

The traces used in this study were collected by instrumenting commercial DBMSs. Instrumenting a DBMS allows the trace information to be collected at a logical level. This method reduces dependencies on the system being traced and allows the trace to be used in a wider variety of studies, including simulations of systems different from the original system. The traces contain references to all database objects (base tables, indexes, temporary spaces, catalogs, views, and plans) except the log. Some of the traces contain references to large pages, i.e., those with sizes that are multiples of the 4KB base page

size. For consistency, we converted these traces to refer to 4KB pages.

In this study, we examined a total of 14 traces representing both industry-standard benchmarks (TPC-C and TPC-D^{1,2}) and the production workloads of ten of the world's largest corporations. The TPC benchmark traces were collected on a multiprocessor personal computer (PC) server running DB2 Universal Database* (DB2/UDB) v5³⁰ on Windows NT** 4.0. The production traces were collected on IBM mainframe computers running various versions of DB2/Multiple Virtual Storage (DB2/MVS), now known as DB2/390.³¹

In order to make our characterization more useful for subsequent mathematical analyses and modeling by others, we fitted our data to various functional forms through nonlinear regression, which we solved by using the Levenberg-Marquardt method.³² When appropriate, we also fitted standard probability distributions to our data by using the method of maximum likelihood to obtain parameter estimates and then optimizing those estimates by the Levenberg-Marquardt algorithm.³²

Trace collection. We instrumented DB2/UDB at the source level to collect relevant trace information for the TPC benchmarks. Because the act of tracing a system may affect its behavior, we paid special attention to minimizing any such disturbances. For instance, our tracing facility collects the trace records in shared memory before batch writing them asynchronously to disk. The shared memory buffer is double-buffered so that trace collection is not blocked during write-backs. Each trace record is time-stamped with minimal overhead by directly accessing the processor cycle counter. At certain trace points, it is expensive to collate all the interesting information. In such cases, enough data are written to the trace so that an off-line postprocessing step can be used to reconstruct the information. We collected trace records for both logical and physical reads and writes, prefetch requests initiated by DB2, references to the database log, and transaction starts and ends. By comparing the TPC-C throughput results when trace collection is enabled and disabled, we estimate that this tracing mechanism imposes an overhead of less than 5 percent. This figure is dramatically lower than tracing overheads that have been previously observed; GTF (Generalized Trace Utility) tracing can require over 50 percent of the CPU time.

The production traces were collected using a custom DB2/390 tracing package developed at the IBM Almaden Research Center. This tracing package was designed to collect trace data with a minimum amount of overhead so that it can be run on customer production systems with little throughput impact. It was built upon the existing DB2 Instrumentation Facility and its performance trace.³³ The basic approach is to use a DB2 exit routine to collect the required data from a specially instrumented DB2 build. The collected data are assembled into trace records and stored in large memory buffers that are written out by a separate task operating asynchronously in another address space. This tracing package collects trace records for buffer manager requests, transaction boundaries, and locking events. In tests conducted on an IBM 4381-T92 when handling a DB2 transaction-oriented workload at 70 percent CPU utilization, the trace collection added only about 4 percent to the CPU utilization.

The buffer pool interface in both DB2/UDB and DB2/390 allows pages to be “fixed,” or pinned, in memory.^{34,35} Once a page is fixed, the buffer pool interface can be bypassed so that data within the page can be directly manipulated by the various DBMS components. Such bypassing allows the DBMS components to use the buffer pool as working storage, thereby eliminating the need for the components to make local copies of the data. Consequently, there are references within the pinned pages that result from direct manipulations by the DBMS components that are using the buffer pool as working storage. Since our traces were collected at the level of the buffer pool interface, they do not contain such references that reflect the direct use of buffer pool storage as working storage.

Workload description. The TPC-C benchmark models the operational end of the business environment where real-time transactions are processed.¹ It is set in the context of a wholesale supplier and is centered around its order-processing operations consisting of business transactions that enter new orders, query the status of existing orders, deliver outstanding orders, enter payments from customers, and monitor warehouse stock levels. The TPC-C performance metric is the number of orders processed per minute. The benchmark specifies a method for scaling the database based on an assumed business expansion path of the supplier. Our particular trace was collected on a benchmark set up with a scale of 800 warehouses.

The TPC-D benchmark models the analysis end of the business environment where trends are analyzed and refined to support sound business decisions.² The TPC-D database is a decision support database that tracks, possibly with some delay, the OLTP database through batch updates. The benchmark consists of 17 read-only queries that are far more complex than most OLTP transactions and that typically examine large volumes of data using a rich set of operators and selectivity constraints. To exercise the update functionality of the DBMS, the benchmark includes two update functions that modify a small percentage of the database. The TPC-D benchmark defines both a power test to measure the raw query execution power of a system with a single active user and a throughput test that may be omitted. Our trace captures the entire run of a power test. This test starts off with the first update function (UF1). Next, the 17 queries are processed in a sequence specified by the benchmark. Finally, the second update function (UF2) is executed.

As with TPC-C, the TPC-D benchmark specifies a method for scaling the database. Our trace was collected on a system with a scale factor of 30, which means that the two largest tables, ORDER and LINEITEM, contained 45 million and 180 million tuples, respectively. In general, the actual workload imposed on the system varies with the scale factor and could lead to very different strategies or plans for performing the queries. Although the analysis presented in this paper is specifically for a scale factor of 30, we believe that most of the qualitative results apply to other scale factors as well.

More details about the benchmarks can be found in Reference 7 and in the benchmark specifications.^{1,2} Note that the TPC benchmark rules prohibit publicly disclosing TPC performance figures that have not been independently audited. Therefore, we withhold from this paper any data that may be used to derive our TPC metrics. This omission of absolute TPC performance numbers should not compromise our understanding of the logical characteristics of the benchmarks.

Our other traces were collected in the day-to-day production environments of a diverse group of very large corporations. The industries represented include aerospace, banking, consumer goods, direct mail marketing, financial services, insurance, retail, telecommunications, and utilities. In all cases, our traces include the peak production database workload as identified by the system managers. This work-

Table 1 Summary of trace characteristics

Trace	Aerospace	Bank	ConsGds	DirMktg1	DirMktg2	FinSvcs	Insurance	Retail	TelecomA	TelecomB1	TelecomB2	Utility	Prod. Ave.	TPC-C	TPC-D
Source	Aerospace company	Banking corp.	Consumer goods company	Direct mail marketing firm	Direct mail marketing firm	Financial services firm	Insurance company	Discount store	Telecom. company A	Telecom. company B	Telecom. company B	Utility company	—	TPC benchmark C	TPC benchmark D
Platform	MVS on IBM S/370	MVS on IBM S/370	MVS on IBM S/370	MVS on IBM S/370	MVS on IBM S/370	MVS on IBM S/370	MVS on IBM S/370	MVS on IBM S/370	MVS on IBM S/370	MVS on IBM S/370	MVS on IBM S/370	MVS on IBM S/370	MVS on IBM S/370	WinNT on Intel X86	WinNT on Intel X86
DBMS	DB2/MVS	DB2/MVS	DB2/MVS	DB2/MVS	DB2/MVS	DB2/MVS	DB2/MVS	DB2/MVS	DB2/MVS	DB2/MVS	DB2/MVS	DB2/MVS	DB2/MVS	DB2/UDB	DB2/UDB
Date Collected	2/3/1992	5/13/1991	9/8/1992	9/18/1991	9/19/1991	6/6/1991	10/7/1992	7/1/1992	4/15/1992	10/8/1990	10/9/1990	5/14/1991	—	2/10/1998	3/8/1998
Duration (h:m)	2:29	22:57	1:59	1:03	2:02	3:54	2:41	4:52	1:40	2:27	1:42	3:16	4:15	(withheld)	(withheld)
# Objects	2203	1281	626	1446	1446	3124	1953	434	521	255	1139	1224	101	192	
Data Size (MB)	33558	53079	3423	18191	18191	10064	38095	72188	197422	15114	15114	39070	42792	70246	77824
Footprint (MB)	1397	9600	726	1137	1362	2127	1732	6769	2986	947	976	5727	2957	13267	51580
# References	7779007	35916414	7133845	6401880	14396125	15664004	20648874	38646360	13072916	11531195	13757374	37653369	18550114	196067649	218130354
# Xacts	98931	85173	66102	11892	14906	20956	70242	797637	84378	36508	25899	118191	119235	890885	230
Read Ratio (%)	93.8	90.6	86.9	95.4	95.6	90.9	84.8	86.9	85.9	93.0	98.1	89.3	90.9	87.4	97.8

load is typically a combination of transaction processing and long-running queries. The trace referred to as Telecom in Zivkov and Smith¹⁶ and Phone in Singhal and Smith¹⁷ is the first 30 minutes of the trace we call TelecomB1.

Trace description. Table 1 summarizes the characteristics of the various traces that are used in this paper. Because of the large number of production workloads, we often also present the arithmetic mean of their results, denoted as “Prod. Ave.” In the table, the term *object* refers to a logical collection of data, such as a database table or an index, that is managed as an entity in much the same way as a file. *Data size* represents the total size of all the objects in the system and was obtained from the catalog dumps that were taken when the systems were traced. The *footprint* of a trace is defined as the amount of data referenced at least once in the trace. The traces record information from the perspective of the DBMS. Therefore, the object count includes DBMS system objects such as catalogs, views, and query plans. In addition, the transactions recorded are database transactions, several of which may be needed to perform a single business transaction.

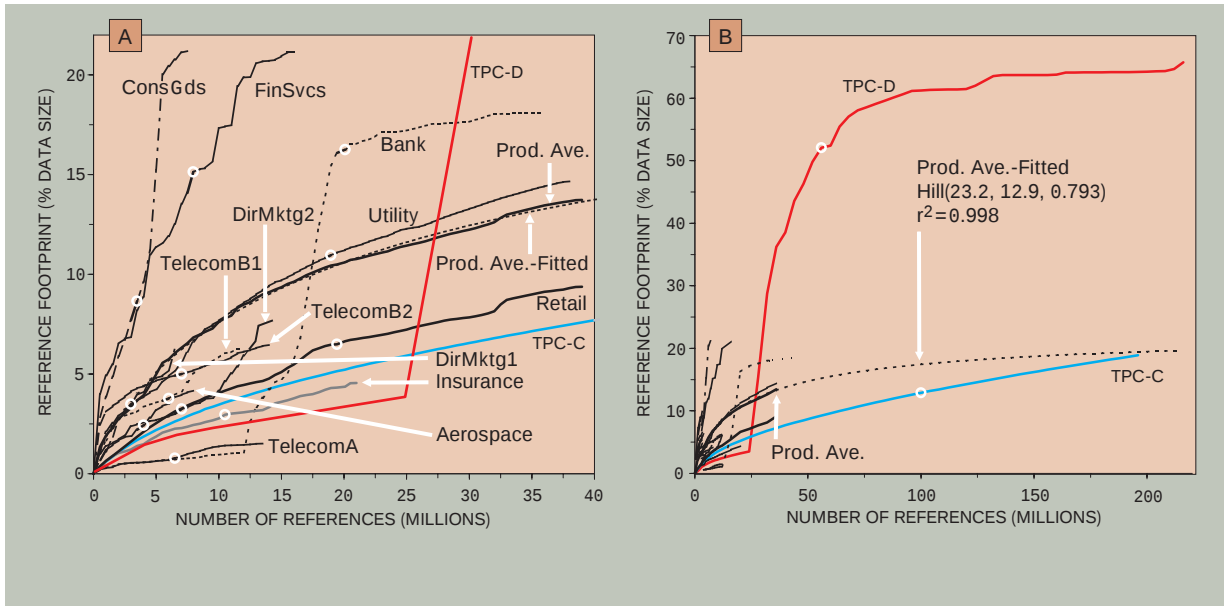
The production traces were taken from the primary systems in use at some of the world’s largest corporations in the early 1990s. These installations had some of the highest-end IBM mainframe systems available at the time. Unfortunately, we do not have information regarding their exact system configurations. Note that the mainframe platform is very different from the PC platform on which our benchmark traces were collected. MVS has its roots in the IBM System/360* architecture and was originally designed to provide full support for large-scale batch processing in production environments. Windows NT, in con-

trast, is a recent operating system with a built-in graphical interface that is designed to support interactive use on both workstations and servers. In addition, DB2/MVS and DB2/UDB are two distinct implementations of relational DBMSs. The focus of this paper is on the logical characteristics of the workloads, which should be relatively independent of the physical attributes of the systems. Nevertheless, some dependencies are unavoidable at times, and we note them where appropriate.

By analyzing what is by far the largest set of production traces ever reported in the literature, we believe that our results are illustrative of the actual production workloads in very large corporations in the early 1990s; nevertheless, neither the individual traces nor the averages can be assumed to be typical or representative of any other system. Our data represent only a sample. In addition, given the rapid progress in database technology and applications, especially in the decision support area, workloads from the early 1990s are likely to be different from workloads and benchmarks several years later. For instance, companies are increasingly building their mission-critical applications on standard business application systems rather than directly on database systems. Despite these disclaimers, we believe that most of the characteristics observed in these production workloads are common to many database systems today and that valuable insights are gained by comparing them to the TPC benchmarks.

Figure 1 plots the trace footprint as a function of the number of references, which is a measure of the trace length. Because there is a wide variation in the footprint of our traces, we plot the footprint as a percentage of the total data size of the workload and use two different scales in Figures 1A and 1B to fa-

Figure 1 Reference footprint of the traces as a function of trace length—default warm-start points for the simulations in Reference 5 are circled.



cilitate comparison among the workloads. From the two parts of the figure, only a few of the traces (e.g., TPC-D, Bank, ConsGds, FinSvcs, TelecomA) approach steady state in the sense that they do not appear to be actively referencing new data. Though the artificial nature of TPC-C is apparent in the smoothness of its footprint profile, the rate at which it references new pages is within the spectrum defined by the other traces. The write footprint profiles are presented in Figure 2. These profiles show how the percentage of pages written increases with the number of references. Compared to most of the production traces, the TPC traces generate modified pages at a much higher rate. We examine the write behavior of the various workloads in greater detail in Reference 5.

An important issue in using trace-driven simulations to study memory hierarchy design is that the traces must have a sufficiently large footprint for the memory configurations of interest. However, estimating the length of trace required is difficult because the relationship between the trace length and footprint is not well understood. In this paper, we empirically determine this relationship by looking at the average footprint of our production traces. Because the traces are of different lengths, the number of traces being averaged will decrease with the trace length

so that the resulting curve will contain discontinuities if we simply average the footprints. Therefore, we take the average of the rate of increase of the footprint and then integrate the resulting expression. More formally, we define the average footprint after X references as

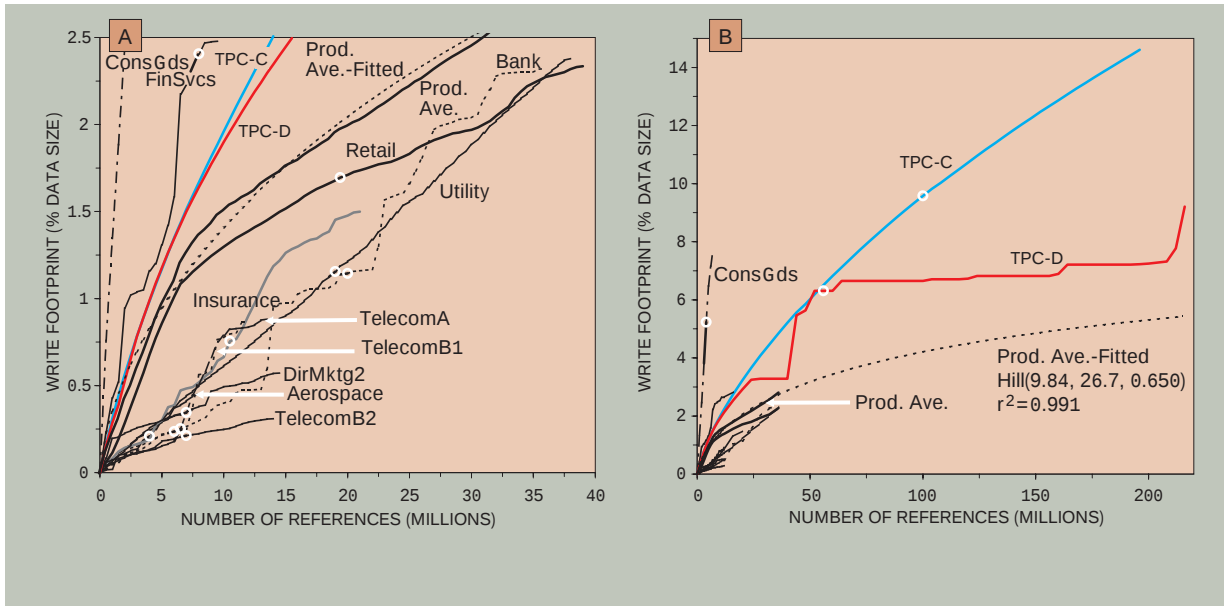
$$\int_0^X \frac{d}{dx} (f_i(x)) dx$$

where $f_i(x)$ denotes the footprint of trace i after x references. This expression is plotted as the lines labeled “Prod. Ave.” in Figures 1 and 2. Note that we omit “Bank” in plotting the average because its footprint profile is distinct from any of the other production workloads.

We find that the relationship between trace length and footprint can be accurately described by the Hill equation that was originally proposed for modeling the absorption of oxygen by hemoglobin.³⁶ The Hill model, $Hill(f_{max}, k, n)$, represents a family of sigmoidal saturation curves defined by

$$f(x) = \frac{f_{max} \cdot x^n}{k + x^n}$$

Figure 2 Write footprint of the traces as a function of trace length—default warm-start points for the simulations in Reference 5 are circled.



where f_{max} is the asymptotic value of $f(x)$ and k and n are parameters that determine the shape and slope of the curve. In our current context, the value of f_{max} represents the percentage of data that is predicted to be in active use. For instance, from Figure 1, the model predicts that 23.2 percent of the data will be referenced if the trace is infinitely long. From Figure 2, the model predicts that only 9.84 percent of the data will be written to.

Workload characteristics

In this section we describe the various characteristics of our workloads.

Transaction characteristics. Transactions are the building blocks of a database workload. The characteristics of transactions are therefore good reflections of the nature of the workload. Table 2 summarizes the transaction characteristics of our workloads. In this table, we consider the logical read ratio that is defined in terms of references to permanent objects only. Table 2 also contains data on the *page reuse* of transactions. Page reuse is defined as the ratio of the number of references to the number of pages referenced and is an indication of the locality of reference exhibited by the transactions.

The table shows that the production workloads are very diverse in their transaction characteristics. In certain cases, however, TPC-C and TPC-D still fall outside the broad range of behavior exhibited by the production workloads. For instance, the proportion of read-only transactions in the production workloads varies from 19 percent in TelecomA to 90 percent in Utility with an average of about 60 percent. In contrast, only 8 percent of the transactions of TPC-C are read-only. Since read-only transactions are easier to isolate from one another, these percentages suggest that TPC-C stresses the concurrency control mechanism more than the production workloads. Notice also that the TPC-D transactions have a lot more references than those of the production workloads, but they involve fewer objects and have much better locality.

Figure 3 plots the distribution of *transaction size*, which is the number of references in a transaction. The distribution in Figure 3B is weighted in the sense that a transaction of size s is counted s times. Notice that the transactions in the TPC benchmarks, especially those in TPC-D, tend to be larger than those of the production workloads. In addition, the transactions of TPC-D have a wide range of sizes. When two-phase locking is used to ensure that transactions are

Table 2 Transaction characteristics—%tile denotes the percentile at which the average value occurs

Trace		Aerospace	Bank	ConsGds	DirMktg1	DirMktg2	FinSvcs	Insurance	Retail	TelecomA	TelecomB1	TelecomB2	Utility	Prod. Ave.	TPC-C	TPC-D
Xacts	#	98931	85173	66102	11892	14906	20956	70242	797637	84378	36508	25899	118191	119235	890885	230
	% Read-only	76.4	43.4	27.6	74.3	78.2	71.2	81.2	32.3	19.3	60.8	59.7	89.8	59.5	7.96	37.4
Read Ratio (%)	Ave.	95.6	86.0	90.3	96.2	97.0	94.7	96.9	93.1	88.3	95.3	95.1	98.8	93.9	86.5	89.1
	(%-tile)	(22.9)	(48.7)	(54.7)	(21.9)	(19.3)	(24.8)	(15.6)	(39.0)	(38.5)	(36.1)	(35.5)	(10.1)	(30.6)	(54.5)	(59.1)
	Median	100	92.3	88.3	100	100	100	100	94.5	92.6	100	100	100	97.3	84.6	82.2
	Std. Dev.	8.74	13.97	7.99	7.82	7.04	10.1	9.47	7.06	14.6	8.25	8.45	4.59	9.01	4.84	8.74
	90%-tile	100	100	100	100	100	100	100	100	100	100	100	100	100	91.4	100
	10%-tile	80	69.2	80	82.3	85.7	78.0	90.2	83.3	50	85.7	85.2	98.3	80.7	82.8	82.1
# References	Ave.	78.6	422	108	538	966	747	294	48.5	155	316	531	319	376.9	220	948393
	(%-tile)	(90.6)	(96.1)	(78.4)	(91.1)	(90.3)	(97.0)	(90.7)	(86.0)	(95.2)	(88.2)	(90.7)	(93.8)	(90.7)	(58.1)	(92.2)
	Median	4	29	39	24	29	25	32	19	51	49	51	28	31.7	153	63892
	Std. Dev.	4306	15739	381	8889	15968	17602	11708	7951	5439	8948	28885	24724	12545	247	6273027
	90%-tile	68	162	197	433	895	319	257	63	115	400	459	232	300	492	117929
	10%-tile	2	6	7	3	3	4	3	13	4	8	8	3	5.3	26	10
# Pages Ref'd	Ave.	22.3	119	61.6	120	144	152	56.4	16.6	56.6	83.4	74.5	57.7	80.3	73.0	87509
	(%-tile)	(84.6)	(96.3)	(77.2)	(89.7)	(88.5)	(89.8)	(78.9)	(64.7)	(90.7)	(82.5)	(80.0)	(80.6)	(83.6)	(57.9)	(90.9)
	Median	3	28	21	14	15	14	21	13	26	35	36	18	20.3	61	12501.5
	Std. Dev.	439	2715	351	903	1123	1833	366	328	1350	547	743	1517	1018	81.3	484698
	90%-tile	33	90	90	124	242	159	114	29	53	115	117	76	104	161	24776
	10%-tile	2	3	6	3	3	3	3	5	2	7	7	3	3.9	12	4
# Pages Written	Ave.	1.81	12.4	5.93	3.77	6.98	16.0	6.37	2.11	9.88	5.45	4.79	5.66	6.76	16.5	14068
	(%-tile)	(81.5)	(87.6)	(63.4)	(79.7)	(90.0)	(94.0)	(82.8)	(65.5)	(84.8)	(72.5)	(64.8)	(82.1)	(79.1)	(51.0)	(92.6)
	Median	0	3	2	0	0	0	0	1	4	0	0	3	1.1	4	6003
	Std. Dev.	16.2	454	8.77	63.0	178	290	178	141	938	86.5	18.7	306	223	14.7	59347
	90%-tile	3	16	13	6	7	10	13	4	13	8	8	8	9.1	36	6298
	10%-tile	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0
# Obs. Ref'd	Ave.	4.76	11.8	15.6	8.19	8.70	8.40	13.0	7.14	11.4	11.8	12.0	12.9	10.5	10.0	4.6
	(%-tile)	(69.9)	(56.4)	(65.9)	(65.1)	(62.4)	(66.6)	(62.9)	(60.8)	(46.8)	(51.7)	(56.5)	(61.9)	(60.6)	(55.0)	(80.4)
	Median	2	8	8	6	7	6	7	6	12	11	11	7	7.6	7	4
	Std. Dev.	5.43	10.9	14.0	7.29	7.88	8.21	16.2	4.55	7.73	8.42	8.60	12.9	9.34	3.65	3.43
	90%-tile	13	35	37	17	18	18	31	14	21	22	26	29	23.4	14	6
	10%-tile	1	2	2	2	2	2	1	2	2	4	4	2	2.2	7	2.1
Page Reuse	Ave.	1.55	2.12	1.85	2.62	3.18	2.38	1.88	1.73	2.97	3.01	3.26	2.04	2.38	2.75	5.79
	(%-tile)	(74.4)	(80.2)	(60.8)	(74.9)	(77.5)	(73.2)	(70.0)	(60.3)	(92.3)	(87.2)	(87.3)	(65.8)	(75.3)	(63.3)	(86.1)
	Median	1	1.47	1.71	1.45	1.53	1.55	1.36	1.58	2	1.34	1.4	1.79	1.52	2.5	5.11
	Std. Dev.	2.43	5.75	1.08	5.04	9.56	11.6	2.68	1.09	211	5.57	6.09	1.76	22.0	1.17	5.14
	90%-tile	2.05	3.33	2.33	4.6	5.55	3.21	3.34	2.47	2.67	3.81	4.12	3	3.37	3.43	9.17
	10%-tile	1	1	1	1	1	1	1	1	1.25	1	1	1	1.02	1.94	2.75

serializable,³⁷ locks tend to be released only when transactions end so that long transactions typically imply long lock waits. Therefore, the transaction size, which can be considered the virtual transaction length or duration, is a very important factor in analyzing concurrency control mechanisms. To make our data more useful for mathematical modeling, we fitted the data with standard probability distributions. As shown in Figure 3, the lognormal distribution (denoted $\text{LogNorm}(\mu, \sigma)$, where μ is the mean and σ is the standard deviation), turns out to be a good fit.

Since short transactions can be blocked for long periods by long transactions holding the necessary locks, system performance is sensitive to the second and third moments of the transaction size.³⁸ In ad-

dition, the distribution of transaction size affects not only the absolute but also the relative performance of different concurrency control schemes.¹⁷ Therefore, we also present the average and higher moments of the transaction size for our various workloads in Table 3.

In Figure 4, we plot the distribution of the *transaction footprint*, or the number of pages referenced by a transaction. The lognormal distribution is again a good fit. Figures 3 and 4 show that most of the transactions are small, but large transactions account for most of the references and most of the pages referenced. In contrast to TPC-C, the production workloads are made up of transactions with a wide range of sizes and footprints. Such a mixture of large and

Figure 3 Number of references per transaction

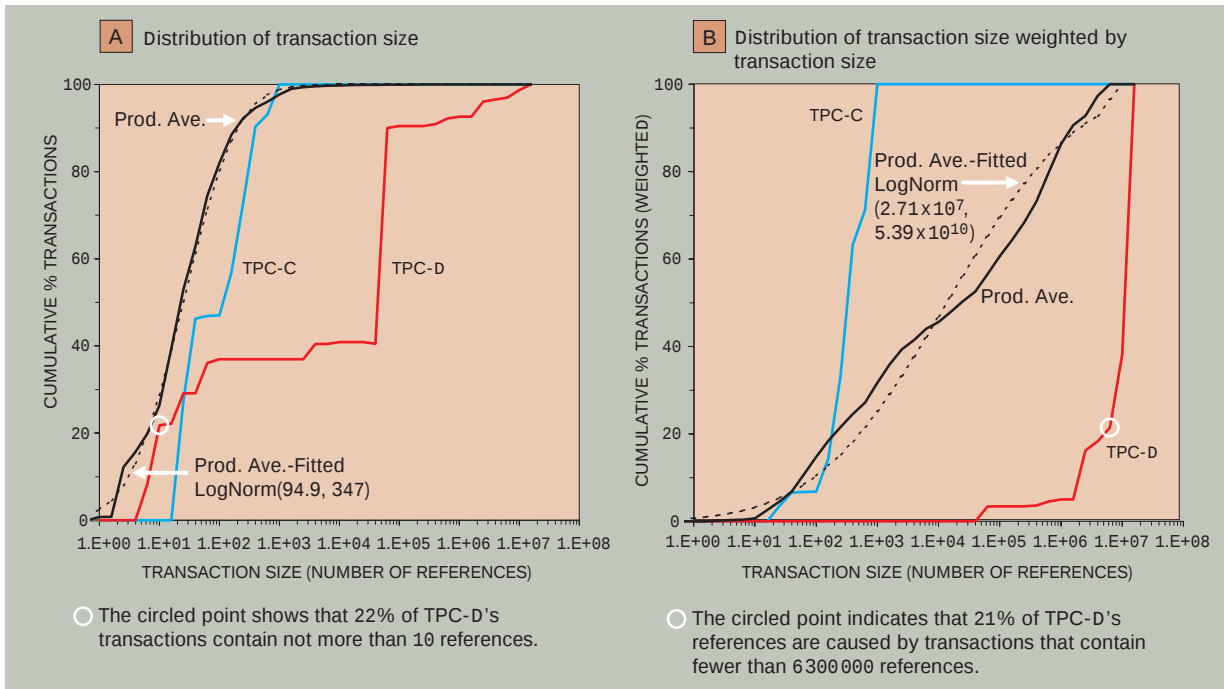


Table 3 First, second, and third moments of the number of references in a transaction (S)

	Aerospace	Bank	ConsGds	DirMktg1	DirMktg2	FinSvcs	Insurance	Retail	TelecomA	TelecomB1	TelecomB2	Utility	Prod. Ave.	TPC-C	TPC-D
E[S]	78.6	422	108	538	966	747	294	48.5	155	316	531	319	377	220	9.48 × 10 ⁵
E[S ²]	1.85 × 10 ⁷	2.48 × 10 ⁸	1.57 × 10 ⁵	7.93 × 10 ⁷	2.56 × 10 ⁸	3.10 × 10 ⁸	1.37 × 10 ⁸	6.32 × 10 ⁷	2.96 × 10 ⁷	8.02 × 10 ⁷	8.35 × 10 ⁸	6.11 × 10 ⁸	2.22 × 10 ⁸	1.09 × 10 ⁵	4.03 × 10 ¹³
E[S ³]	1.65 × 10 ¹³	5.23 × 10 ¹⁴	5.46 × 10 ⁹	3.85 × 10 ¹³	1.79 × 10 ¹⁴	3.98 × 10 ¹⁴	1.97 × 10 ¹⁴	3.93 × 10 ¹⁴	2.12 × 10 ¹³	8.04 × 10 ¹³	2.69 × 10 ¹⁵	2.48 × 10 ¹⁵	5.85 × 10 ¹⁴	7.51 × 10 ⁷	3.04 × 10 ²¹

small transactions complicates the task of scheduling and allocating resources to satisfy the different performance requirements of the transactions. For instance, a suitable balance has to be found between allowing large transactions to make good forward progress and preventing them from monopolizing the buffer pool. Regrettably, this issue is beyond the scope of the current study, which only considers the characteristics of workloads as they have been scheduled and tuned in production environments.

Degree of concurrency. In order to effectively utilize system resources, database systems allow the concurrent execution of multiple transactions through concurrency control mechanisms, such as locking, that provide each transaction with an isolated view of the system. The degree of concurrency, i.e., the number of concurrently active transactions,

in a workload directly affects issues such as lock contention and deadlocks. Furthermore, for each active transaction in the system, the DBMS has to maintain a database agent and its associated context, which is nontrivial and includes various control blocks and private memory. The time-averaged number of transactions that are active in the various workloads at any one time is summarized in the last row of Table 4. The production workloads again exhibit very diverse characteristics with the time-averaged degree of concurrency ranging from slightly below 5 in ConsGds to nearly 80 in Aerospace.

Dynamically creating a database agent can be a significant part of the cost in short- and medium-size transactions. In situations where the degree of concurrency is rather constant, the agents and private resources can be held and reused. Figure 5 shows

Figure 4 Number of pages referenced per transaction

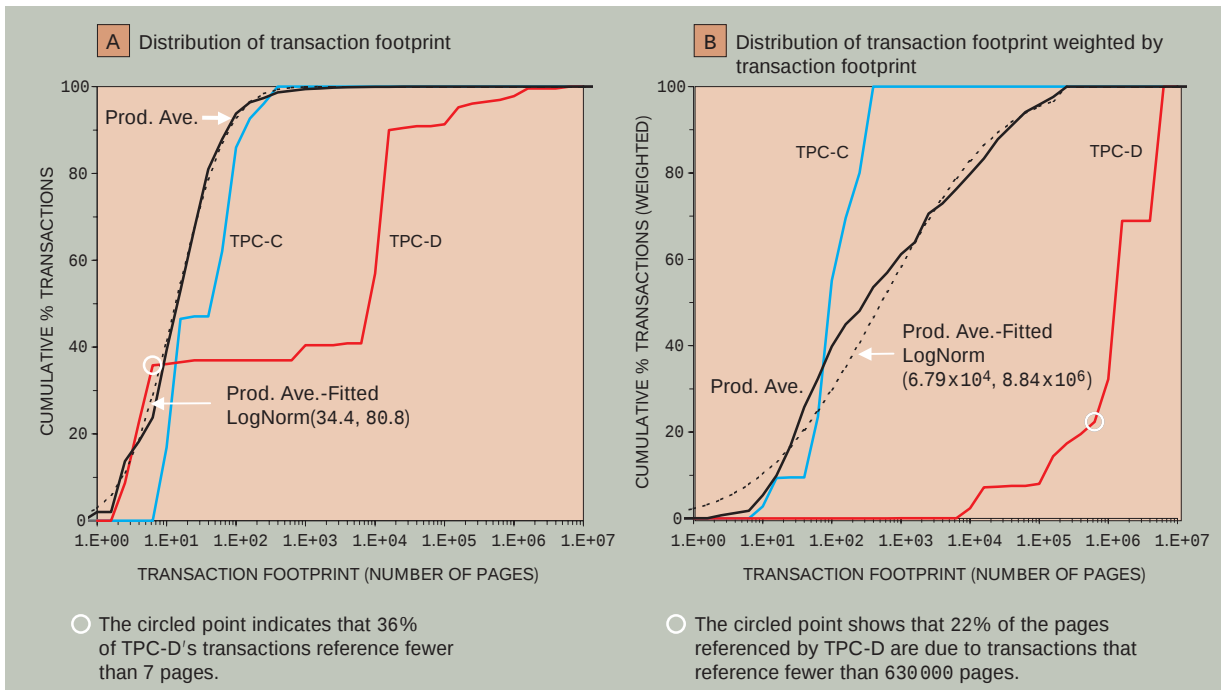


Table 4 Degree of concurrency averaged over various time intervals showing the peak or maximum value observed for each interval size

Trace	Aerospace	Bank	ConsGds	DirMktg1	DirMktg2	FinSvcs	Insurance	Retail	TelecomA	TelecomB1	TelecomB2	Utility	Prod. Ave.	TPC-C	TPC-D
100-ms	131	27.0	15.0	25.0	23.0	48.0	26.0	137	17.0	19.6	16.0	38.9	43.6	60.0	8.00
1-s	128	27.0	12.8	24.3	22.6	48.0	26.0	134	15.4	19.1	16.0	36.0	42.4	60.0	8.00
10-s	125	26.8	11.0	20.9	20.4	47.5	24.3	130	13.8	18.2	14.2	27.7	40.0	60.0	8.00
1-min	124	25.7	8.8	19.7	18.1	33.9	20.7	122	11.6	15.5	12.3	15.9	35.7	60.0	8.00
10-min	119	21.2	7.3	14.0	13.4	29.6	17.2	79.1	8.9	9.4	8.0	13.2	28.4	60.0	8.00
100-min	108	11.0	5.0	12.2	11.9	25.9	13.2	53.5	5.7	6.4	6.4	12.3	22.7	60.0	5.59
Trace Len.	77.7	5.39	4.91	12.1	11.6	20.5	12.8	42.7	6.50	5.06	6.32	11.3	18.1	60.0	3.07

how the degree of concurrency in the various workloads varies over time. The very static profiles for both TPC-C and TPC-D stand in stark contrast to those of the production workloads and imply that the TPC benchmarks will not exercise the agent creation process of the DBMS. For a more quantitative characterization of the extent to which the degree of concurrency fluctuates over time, we time-averaged the degree of concurrency over intervals ranging from 100 milliseconds to the trace length. The maximum values observed for each of these interval sizes are presented in Table 4. We also plot the distribution of the degree of concurrency time-averaged over one-second periods in Figure 6. As shown in the fig-

ure, the lognormal distribution is a reasonably good fit for the average of the production workloads.

Object characteristics. For performance reasons, most DBMSs offer an option to bypass the file system provided by the operating system to directly access the raw storage devices. In this case, the DBMS provides its own basic file system functionality such as allocating storage and tracking free space. In this subsection, we look at the characteristics of the objects in the various workloads to better understand what is required of the underlying file system, whether it is provided by the operating system or the DBMS.

Figure 5 Profile of degree of concurrency over time—data show rates averaged over one-minute intervals, not instantaneous rates.

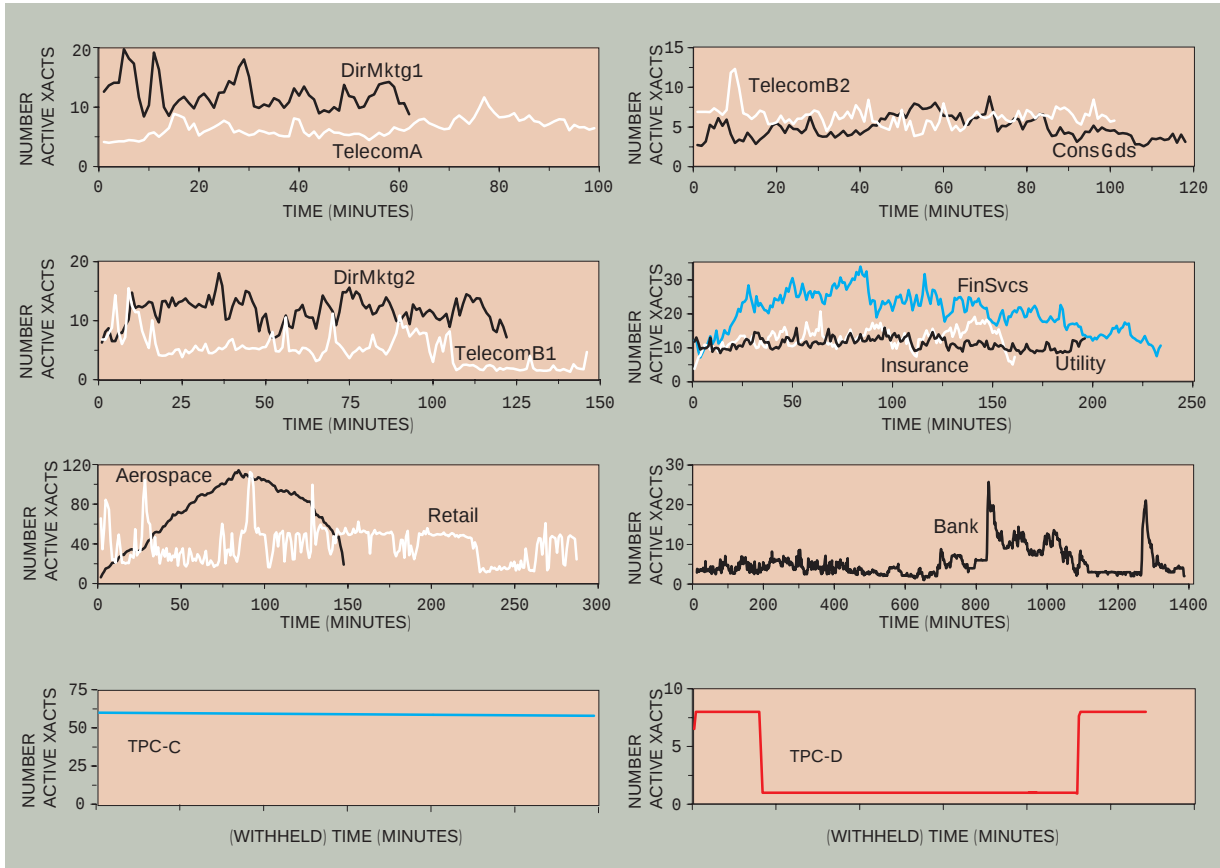


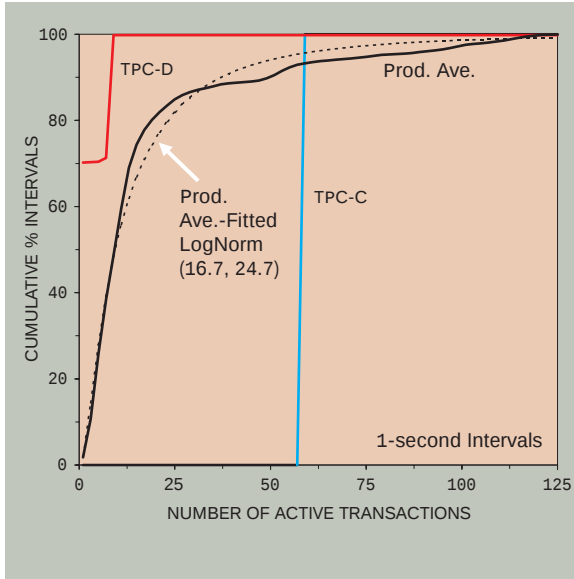
Table 5 Reference activity on object and page bases

Trace		Aerospace	Bank	ConsGds	DirMktg1	DirMktg2	FinSvcs	Insurance	Retail	TelecomA	TelecomB1	TelecomB2	Utility	Prod. Ave.	TPC-C	TPC-D
Objects	Total #	2203	1281	626	1446	1446	3124	1953	434	521	255	255	1139	1224	101	192
	% Ref'd	42.9	79.5	39.6	32.3	36.3	35.2	39.7	43.8	48.6	60	62.0	54.3	47.9	15.8	37.5
	% Modified	22.0	37.9	20.6	15.3	16.0	14.5	21.3	24.4	26.9	36.1	38.4	36.3	25.8	11.9	22.9
Pages	Total #	8590909	13588236	876401	4656812	4656812	2576270	9752447	18480252	50539937	3869199	3869199	10002028	10954875	17982935	19922913
	% Ref'd	4.16	18.1	21.2	6.25	7.49	21.1	4.55	9.38	1.51	6.27	6.46	14.7	10.1	18.9	66.3
	% Modified	0.45	2.32	7.78	0.34	0.57	2.83	1.50	2.33	0.882	0.864	0.310	2.38	1.88	14.6	9.93

The total number of objects and the fraction of them that are referenced or modified are presented in Table 5. The total object count was obtained from the catalog dumps that were taken when the systems were traced. Notice that the production workloads have significantly more objects than the two benchmarks. This observation is not surprising because the benchmarks are supposed to be distillations of real

environments and should therefore contain only the core portions of real workloads. Furthermore, the benchmark traces were collected on DB2/UDB, which considers the various indices of a table as a single object instead of individual objects. Figure 7 presents the distribution of object size. Observe that the object size, like the transaction size, tends to approximately follow a lognormal distribution. In addition,

Figure 6 Distribution of degree of concurrency time-averaged over one-second intervals—distribution for one-minute intervals is virtually identical.



most of the objects are small, but the very large objects account for most of the bytes. This behavior is similar to what has been observed in a general UNIX** file system, although the scale there is much smaller.³⁹ Interestingly, the distribution of file sizes in PCs running Microsoft Windows** in an office environment has also been recently reported to follow a lognormal distribution, but the files are again much smaller than the objects in the database workloads.²⁷

Notice from Table 5 that, for most of the workloads, less than half of the objects are referenced for the duration of the trace. In general, a common approach to improving computer system performance is to place the items that are likely to be used in faster storage. At the system level or, in other words, external to the DBMS, we can statically allocate to faster storage (e.g., solid-state disks) the hottest objects, i.e., those with the highest density (rate per byte) of reference. This approach reflects what has been referred to as the “ $\lambda_{i,j}$ ” model⁴⁰ in which a transaction stream i references object j as a Poisson process with rate $\lambda_{i,j}$. Under such a model, an optimal static allocation should give nonlookahead optimal results,

Figure 7 Size of the objects in the various workloads

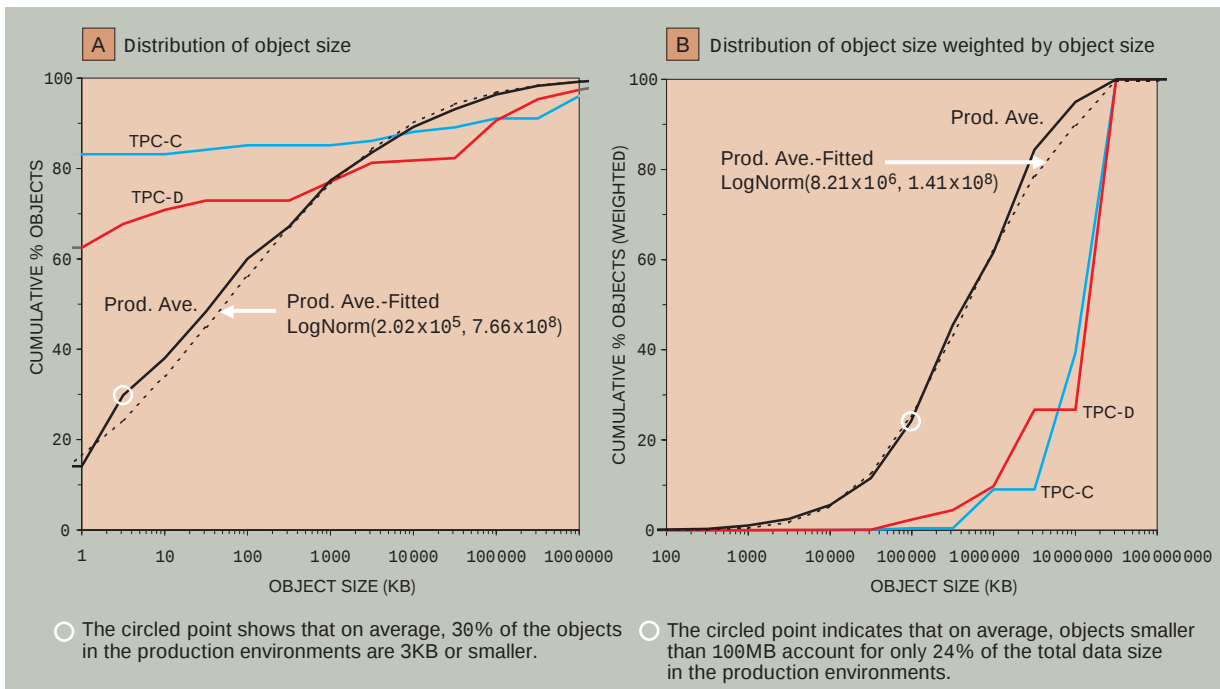
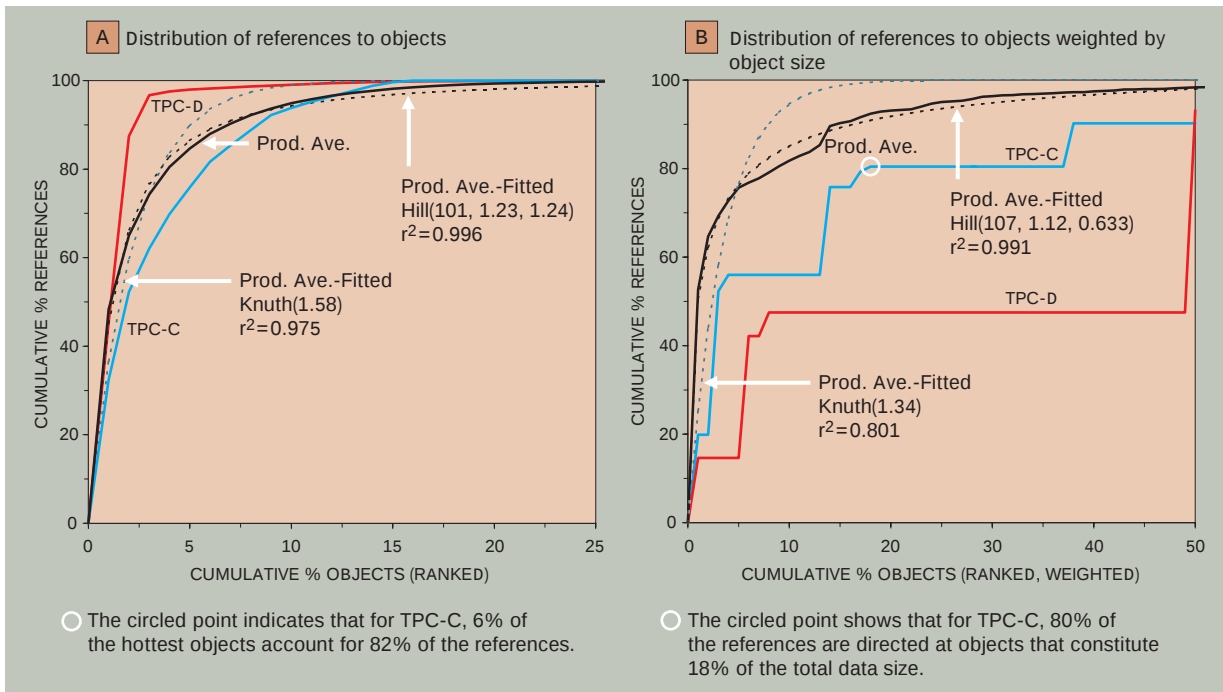


Figure 8 Reference skew on an object basis



as with the A_o algorithm for the independent reference model for program behavior.⁴¹ We consider the performance potential of such an approach in Figure 8.

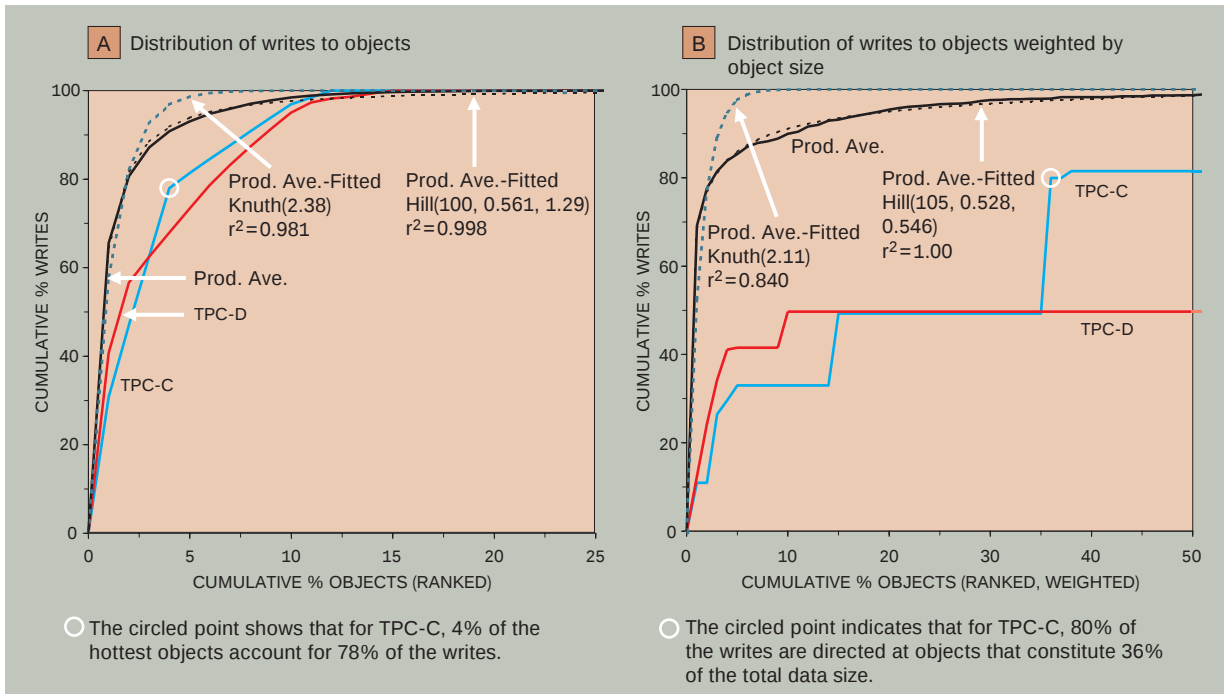
Figure 8A shows that a small number of objects account for most of the references. This skew in the access pattern is common in computer systems and has been expressed as the “90/10” or “80/20” locality rule. For instance, in 1971, Knuth observed that the n th most important statement in a set of FORTRAN programs accounts for $(\alpha - 1)\alpha^{-n}$ of running time, where α is a parameter.⁴² We refer to this model of reference skew as the Knuth(α) model. As shown in Figure 8A, we fitted the data for our production workloads with this function. Since the fit is not very good, we also experimented with more complicated functions. It turned out that the Hill equation³⁶ discussed earlier is a much better fit.

Since the objects are of different sizes, we need to account for their sizes to fully understand the potential benefit of allocating hot objects to faster storage. This accounting is done in Figure 8B where an object of size s is considered to be s objects. Notice

that the production workloads on average have a much higher reference skew than the two TPC benchmarks. This difference suggests that the production workloads will generally be more amenable to strategies that attempt to statically optimize data placement on an object basis. In Reference 5, we further consider the static management of faster storage on a page basis, and the results indicate that dynamic management offers a dramatically better hit ratio. This outcome is in line with conclusions in Smith⁴⁰ and indicates that reference probabilities are clearly time-varying and that the $\lambda_{i,j}$ model, like the independent reference model for programs, is not valid.

The write skew for our workloads is plotted in Figure 9. As is the case for the reference skew, we find that the write skew can be accurately described by the Hill equation. From Figure 9B, we see that the write skew taking into account the size of the objects is generally less pronounced than the reference skew but is still very significant for the production workloads. Again, the two TPC benchmarks show much less skew at the object level than do the production workloads.

Figure 9 Write skew on an object basis



In Table 6, we break down the objects into data objects, index objects, and temporary or work file objects. Because of space constraints, we omit the results for the individual production workloads; these results are available in References 6 and 7. Observe that although the data pages account for the majority of pages in most of the workloads, index objects account for the largest chunk of references. This observation suggests that studies that do not consider index references, such as the one by Leutenegger and Dias,¹⁸ may not give the complete picture. Notice further that most of the objects in the production workloads are index objects, but this is not the case in the TPC benchmarks. Part of the reason is that, as mentioned above, the various indices of a table are considered to be a single object in DB2/UDB. Another observation from Table 6 is that the temporary objects may account for up to 80 percent of the write traffic and must therefore be considered when characterizing the write behavior of the workloads. Furthermore, except for TPC-C, which has no activity to temporary objects, the temporary objects account for a very significant portion of the modified pages.

Note that TPC-D tends to stand out among the workloads. In particular, the ratio of index references to data references in TPC-D is a high 17. Part of the reason is that in the Update Function 1 (UF1) of TPC-D we append the records to be inserted so that it is possible to insert one whole page of records with only one data reference. Perhaps the bigger reason is that so much effort has gone into optimizing TPC-D that we can create indices that contain all the data needed by the queries. This allows “index-only” access where there is no need to probe the base table after an index lookup. In some sense, data are replicated in the indices, which partly explains why our TPC-D setup contains more index pages than data pages. Notice also that less than 1 percent of the modified pages in TPC-D are data pages and that less than 10 percent of the writes update data pages. Instead, most of the updates of TPC-D are directed at index and temporary objects. Such behavior is a reflection of the fact that TPC-D is a query-processing workload that is predominantly read-only and that has been well-tuned to use indices effectively. It implies that optimizations for handling index and temporary objects are disproportionately important for TPC-D.

I/O intensity and burstiness. A major consideration in designing a computer system is that it should be able to sustain I/O activity that is commensurate with its processing power. When designing the System/360, Amdahl observed that the amount of I/O activity generated per instruction tends to be relatively constant.⁴³ More specifically, Amdahl's rule of thumb states that a typical data processing system generates approximately 1 Mb/s of I/O bandwidth for every MIPS (million instructions per second) of processing power.⁴⁴ This rule of thumb dates back to the 1960s, and major changes in both hardware and software have since occurred. Therefore, in this section, we revalidate it by empirically estimating the ratio of I/O activity to processing power required for our workloads. Note that our trace data reflect only I/O activity generated by the database and not system-generated I/O activity, which may constitute a significant portion of the total I/O activity in certain environments.⁴⁰

We use the term *bPI* (bits per instruction) to denote the number of bits of I/O activity generated per instruction. We emphasize the logical bPI, which is defined in terms of the logical I/O activity generated per instruction. This number is an intrinsic characteristic of the workload and is relatively independent of system configuration such as memory size. Note, however, that dramatic differences in memory size can result in algorithmic changes that affect the logical bPI. For instance, the amount of memory available for sorting determines whether external sorting techniques are required and, if so, the number of merge phases needed.⁴⁵ Similarly, as more memory is available, fewer passes are needed to perform hash joins,⁴⁶ and this translates into less I/O activity and therefore lower bPI. Conversely, with larger and cheaper memories, previously advantageous trade-offs of additional computation for less memory use no longer apply.

Unfortunately, we do not have information regarding the system configurations for our production workloads. We do know, however, that the installations from which our traces were taken tend to have some of the highest-end systems available at the time. So we assume that these systems had about 100 MIPS of processing power, which is roughly half the processing power of the most powerful mainframe systems that IBM began shipping in late 1992. For the TPC benchmarks, the processing power of the systems is determined by the following formula:

Table 6 Relative significance of data, index, and temporary objects

Trace		Prod. Ave.	TPC-C	TPC-D
Objects	Total #	1224	101	192
	% Data	42.7	50.5	60.4
	% Index	55.9	49.5	26.0
	% Temp	1.4	0	12.5
Ref'd. Objs.	Total #	538	16	72
	% Data	42.2	50	44.4
	% Index	56.5	50	19.4
	% Temp	1.2	0	33.3
Modified Objs.	Total #	272	12	44
	% Data	42.0	66.7	40.9
	% Index	55.8	33.3	4.5
	% Temp	2.2	0	54.5
Pages	Total #	10954879	17982935	19922913
	% Data	72.9	84.1	45.2
	% Index	26.7	15.9	50.8
	% Temp	0.4	0	4.1
Ref'd. Pages	Total #	757025	3396262	13204481
	% Data	72.4	74.0	50.8
	% Index	24.9	26.0	43.1
	% Temp	2.7	0	6.1
Modified Pgs.	Total #	153749	2627637	1979231
	% Data	44.6	83.5	0.8
	% Index	31.9	16.5	58.4
	% Temp	23.5	0	40.9
References	Total #	18550114	1.96E + 08	2.18E + 08
	% Data	32.7	28.9	5.4
	% Index	54.8	71.1	92.7
	% Temp	12.5	0	1.8
Writes	Total #	1858947	24723791	4737739
	% Data	28.9	61.7	9.7
	% Index	23.5	38.3	48.8
	% Temp	47.6	0	41.5

$$MIPS = \frac{\# \text{ processors} \cdot \text{processor clock speed}}{\text{estimated CPI}}$$

We estimate that the CPI (cycles per instruction) is about 3.5 for TPC-C and 1.5 for TPC-D, in view of the results presented in References 47 and 48.

The average amount of logical I/O activity generated per instruction for the various workloads is summarized in the last row of Table 7. The corresponding numbers for the write I/O activity are shown in Table 8. On average, the production workloads have a logical bPI of about 0.6, approximately one tenth of which is due to writes. The bPI of TPC-C is about three times higher, whereas the bPI of TPC-D is about twice as high. Note, however, that mainframe and x86 processor MIPS are not equivalent and cannot be directly compared. Our primary interest in this exercise is merely to determine an order-of-magnitude estimate for bPI. We find the number of 0.6 to

Table 7 Number of logical I/O bits per instruction averaged over various time intervals, showing the peak or maximum value observed for each interval size

Trace	Aerospace	Bank	ConsGds	DirMktg1	DirMktg2	FinSvcs	Insurance	Retail	TelecomA	TelecomB1	TelecomB2	Utility	Prod. Ave.	TPC-C	TPC-D
100-ms	2.51	3.46	2.23	3.20	3.73	3.28	5.37	3.72	5.27	3.74	3.97	3.66	3.68	7.11	7.54
1-s	1.76	2.85	1.16	2.09	2.45	2.65	3.19	2.60	3.23	1.89	2.16	2.87	2.41	3.11	6.95
10-s	1.40	1.92	0.632	1.69	1.67	1.65	2.12	1.91	2.81	1.09	1.59	2.40	1.74	2.36	5.66
1-min	0.976	0.878	0.464	1.21	1.42	1.14	1.69	1.29	2.14	0.854	1.32	2.18	1.30	2.05	5.59
10-min	0.575	0.586	0.365	0.848	0.945	0.528	1.25	1.05	1.14	0.683	0.989	1.44	0.867	1.98	3.94
100-min	0.333	0.412	0.335	0.566	0.751	0.437	0.837	0.799	0.540	0.478	0.747	1.08	0.609	1.97	2.22
Trace Len.	0.285	0.142	0.328	0.559	0.643	0.365	0.700	0.724	0.715	0.430	0.739	1.047	0.556	1.89	0.991

Table 8 Number of logical I/O bits written per instruction averaged over various time intervals, showing the peak or maximum value observed for each interval size

Trace	Aerospace	Bank	ConsGds	DirMktg1	DirMktg2	FinSvcs	Insurance	Retail	TelecomA	TelecomB1	TelecomB2	Utility	Prod. Ave.	TPC-C	TPC-D
100-ms	1.14	1.06	0.492	0.963	0.796	2.01	1.25	0.816	1.41	0.800	0.731	2.22	1.14	0.789	1.16
1-s	0.559	0.664	0.193	0.583	0.494	1.15	0.820	0.623	1.05	0.684	0.634	1.83	0.774	0.415	0.767
10-s	0.311	0.383	0.109	0.305	0.307	0.394	0.592	0.270	0.499	0.146	0.143	1.38	0.403	0.305	0.208
1-min	0.0821	0.332	0.0785	0.128	0.157	0.277	0.409	0.196	0.305	0.110	0.0562	0.726	0.238	0.262	0.173
10-min	0.0289	0.189	0.0525	0.0386	0.0468	0.0648	0.299	0.154	0.192	0.0743	0.0248	0.233	0.117	0.250	0.0578
100-min	0.0212	0.051	0.0421	0.0261	0.0358	0.0554	0.154	0.0985	0.0548	0.0444	0.0146	0.137	0.0612	0.248	0.0301
Trace Len.	0.0178	0.0134	0.0430	0.0260	0.0282	0.0333	0.106	0.0951	0.101	0.0303	0.0141	0.112	0.0517	0.239	0.0215

be surprisingly high—almost as high as the earlier noted number of 1.0, based on systems of the 1960s, despite all of the changes suggesting much lower I/O rates.

The physical bPI for a given system configuration can be obtained from the logical bPI by multiplication with the buffer pool miss ratio. Results presented in Reference 5 show that a buffer pool that is 1 percent of the total data size can achieve an average hit ratio of about 90 percent for the production workloads. With such a hit ratio, the average physical bPI value for the production workloads appears to be around 0.06, which is much lower than Amdahl's rule of thumb. In the 1960s, of course, physical and logical I/O activity were the same thing. The corresponding hit ratio for the TPC benchmarks is around 95 percent, meaning that the physical bPI for TPC-C and TPC-D is comparable to the average of the production workloads (0.09 for TPC-C and 0.05 for TPC-D).

The burstiness of the I/O traffic is a very important characteristic of a workload and has implications on the techniques that can be applied to improve I/O performance. For instance, a bursty traffic pattern suggests that buffering mechanisms that smooth out the traffic will be useful. More generally, it indicates that there are opportunities to use the relatively idle periods to do some useful work. One common approach is to defer or off-load some work from the busy periods to the relative lulls. Write buffering with subsequent destage and logging disk arrays⁴⁹ can be

viewed as examples of such an approach. Another frequently used approach is to eagerly or speculatively perform some work in the hope that such work will help improve performance during the next busy period. Examples of such techniques include pre-fetching, reorganizing data based on access patterns, and garbage collection. A bursty traffic pattern may also be more amenable to techniques that adjust and adapt to the traffic. For instance, if the write traffic is bursty, setting aside a fixed portion of the buffer pool as the write cache will probably not perform as well as letting the write cache grow and dynamically deciding when and what pages to destage.

In this paper, we briefly consider how the workloads vary in the burstiness of their I/O traffic. Readers who are interested in the detection of idle periods and the prediction of their lengths are referred to Golding et al.⁵⁰ Figure 10 shows the profile of logical bPI over time. Observe that the I/O traffic of the production workloads tends to be rather bursty in nature. Because of time-of-day effects, the fluctuation in bPI is especially pronounced for Bank, which was observed for 23 hours. The I/O traffic for TPC-D is also very bursty. In contrast, the I/O traffic of TPC-C stands out as being very regular, suggesting that TPC-C, unlike the production workloads, will not discriminate against systems that do not exploit the idle periods.

For a more quantitative characterization of the burstiness, we time-averaged the logical bPI for the

Figure 10 Profile of number of logical I/O bits per instruction over time—data have been smoothed by averaging over one-minute intervals.

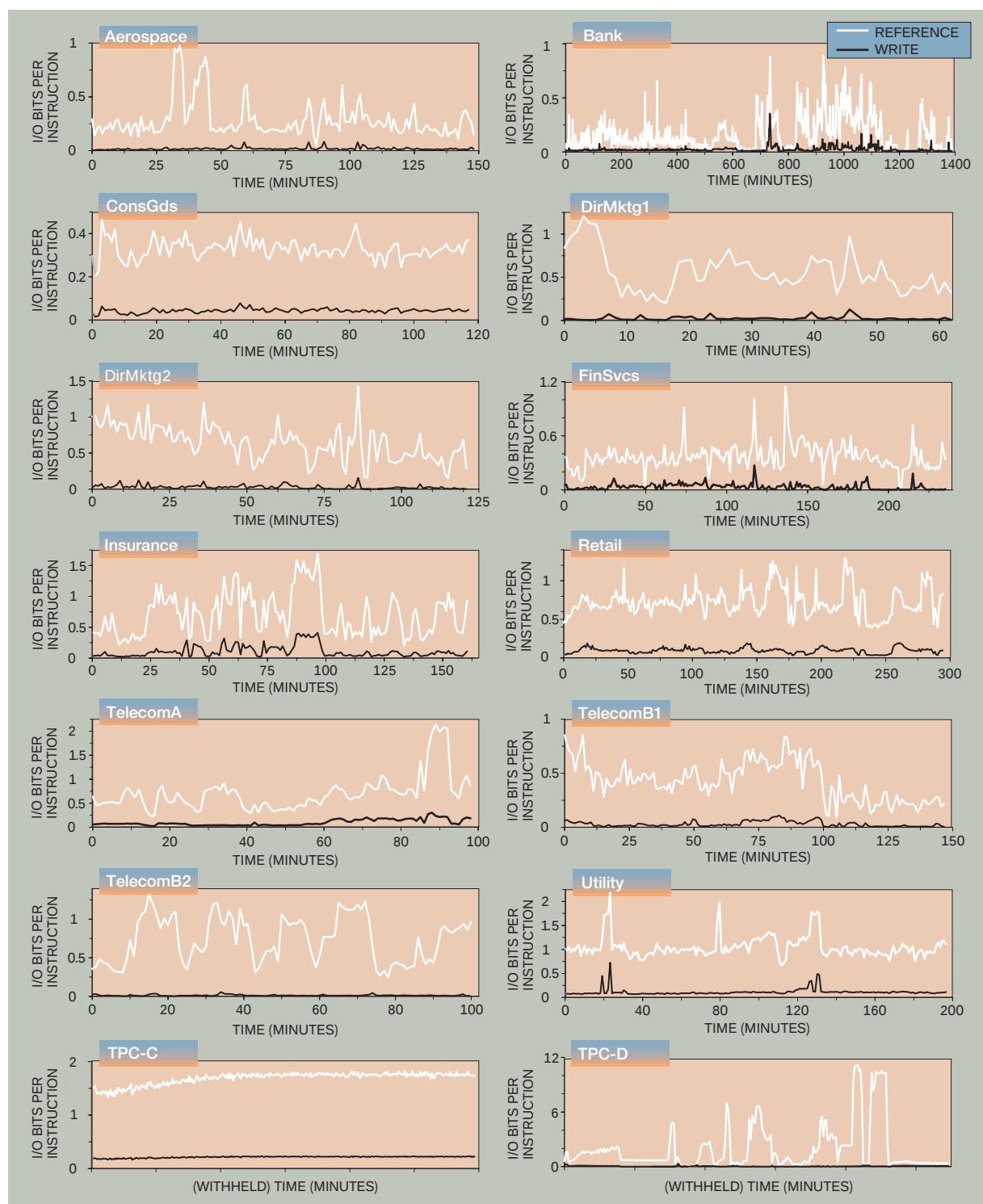
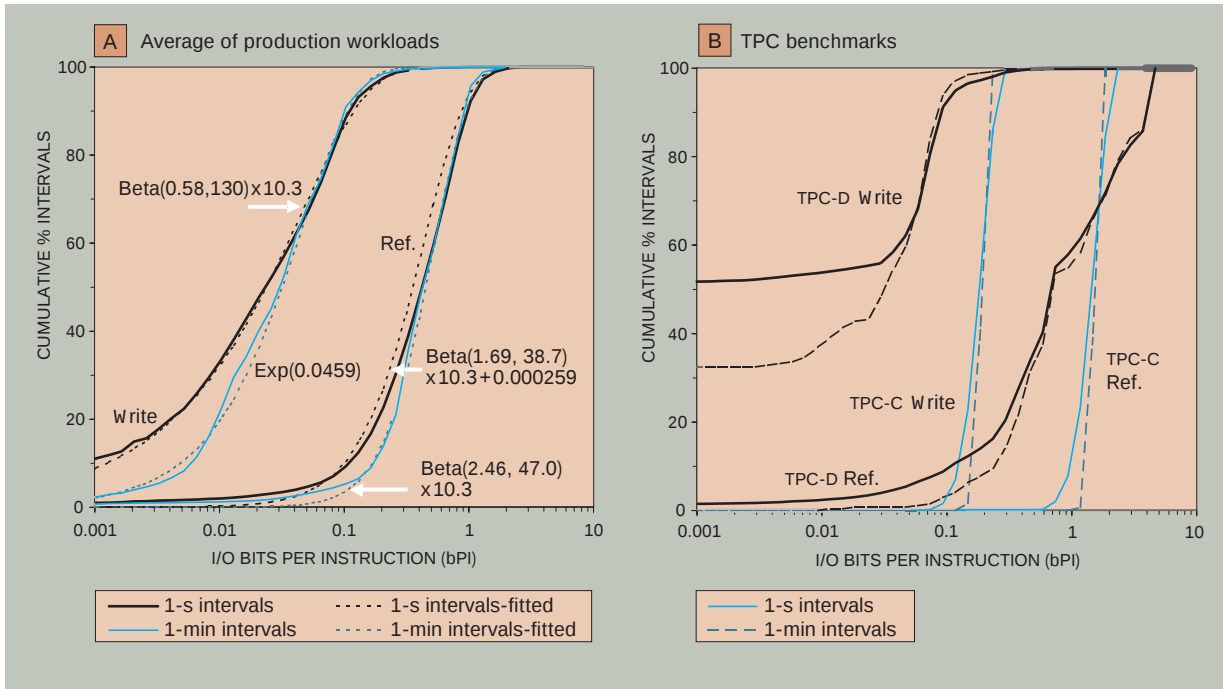


Figure 11 Distribution of number of logical I/O bits per instruction averaged over one-second and one-minute time intervals



various workloads over intervals ranging from 100 milliseconds to the trace length. The maximum values observed for each of these intervals are presented in Tables 7 and 8. The fact that the bPI drops significantly when averaged over longer time periods indicates that the I/O traffic of the workloads tends to be very bursty in nature. When designing systems, we have to take this burstiness into consideration and design not just for the average case. Notice further that writes account for a larger fraction of the bPI for smaller interval sizes, suggesting that write activity is more bursty than read activity.

Figure 11 plots the distribution of the number of logical I/O bits per instruction averaged over one-second and one-minute periods. As shown in the figure, the data can be modeled reasonably well by the beta distribution (denoted $\text{Beta}(\alpha_1, \alpha_2)$, where α_1 and α_2 are the standard parameters) and the exponential distribution (denoted $\text{Exp}(\mu)$, where μ is the mean). For instance, the distribution of bPI averaged over one-second periods tends to follow the beta distribution with parameters 1.69 and 38.7 that is scaled by 10.3 and translated by 0.000259. This distribution is denoted as $\text{Beta}(1.69, 38.7) \times 10.3 + 0.000259$ in Figure 11.

Conclusions

In this paper, we empirically examine the workload characteristics of the peak production database workloads of ten of the world's largest corporations as well as those of the industry-standard benchmarks for on-line transaction processing and decision support systems, namely TPC-C and TPC-D. Even though the production workloads were run on similar systems at around the same point in time, they turned out to be very diverse. Nevertheless, in certain cases, TPC-C and TPC-D still fall outside the broad spectrum of behavior exhibited by the production workloads. In general, the two TPC benchmarks tend to complement one another in the sense that they are representative of different aspects of the production workloads. However, there are still some characteristics of the real workloads that are not reflected by either of the benchmarks.

Specifically, we find that the production workloads are dynamic in that their characteristics are time-varying. For instance, their I/O demands are very bursty, suggesting that adaptive techniques for smoothening the load and for intelligently exploiting idle periods will be useful in a production set-

ting. In stark contrast, TPC-C is very static and predictable, implying that TPC-C primarily evaluates peak performance, which though definitely important, does not translate exactly into effective performance in a production environment with bursty workload characteristics. TPC-D is better in this regard, but it shares with TPC-C the characteristic of having a rather stable degree of concurrency. As a result, these benchmarks will tend not to measure the overheads for setting up and destroying database agents, which can be significant in production environments.

Another aspect of the regularity of TPC-C is manifested in the size of its transactions. Unlike the production workloads that contain transactions with a wide variety of sizes, the transactions of TPC-C are very uniform in size. In other words, TPC-C will not test techniques for scheduling and allocating resources among transactions with different resource and performance requirements even though these techniques are important in the production environments. TPC-D appears to be similar to the production workloads in that it contains transactions with a wide variety of sizes. However, the very long transactions in TPC-D are caused by the read-only queries that are run serially in the power test. Therefore, it too does not evaluate scheduling and resource allocation among diverse transactions.

When two-phase locking is used to ensure that transactions are serializable,³⁷ locks tend to be released only when transactions end. Therefore, the distribution of transaction size is a very important factor in determining lock contention. As we have seen, the transactions of TPC-C are rather uniform in size. Furthermore, when compared to the production workloads, TPC-C tends to have longer transactions and relatively few read-only transactions. All these suggest that TPC-C stresses the concurrency control mechanism differently than the production workloads analyzed in this paper. Some of the transactions of TPC-D are much longer than those of the production workloads, but since they are read-only, they can be run at a lower isolation level, i.e., under more relaxed consistency requirements.⁵¹ Furthermore, in the TPC-D power test, the long transactions are run serially so that TPC-D tends not to load the concurrency control mechanism.

Although temporary objects account for a significant portion of the write traffic in the production workloads, TPC-C does not have any activity to temporary objects. TPC-D is more in line with the production workloads in this regard, but it stands out in having

practically all of its references directed at the index objects. All these factors indicate that TPC-C does not assess the handling of temporary objects, whereas TPC-D disproportionately rewards index optimizations. Our analysis also suggests that on an object basis, the production workloads exhibit significantly higher reference and write skew than do the two benchmarks. In other words, statically allocating hotter objects to faster storage will be more beneficial to the production workloads than to the TPC benchmarks.

As part of our analysis, we also re-examine Amdahl's rule of thumb from the 1960s, which states that a typical data processing system generates about 1 Mb/s of I/O bandwidth for every 1 MIPS of processing power. We discover that both the TPC benchmarks and the production workloads generate logical I/O rates within a factor of two of the earlier figure, despite the passage of 20 to 30 years. Physical I/O rates, of course, are about 90 percent lower due to the use of buffering and caching techniques not used in the earlier period.

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**Trademark or registered trademark of Transaction Processing Performance Council, Microsoft Corporation, or X/Open Company Ltd.

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